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A Hybrid AI-Blockchain Framework For Securing Industrial Iot Devices

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Abstract– *The rapid expansion of Industrial Internet of Things (IIoT) networks has introduced significant security vulnerabilities, as traditional authentication methods often prove inadequate (Derrick Lim Kin Yeap et al., 2024). These challenges pose risks to data integrity, confidentiality, and access control within industrial processes that rely on interconnected smart sensors and actuators (Ahamed Aljuhani et al., 2024). Current systems struggle with securing communication, managing device identities, and preventing threats like unauthorized access and data breaches across insecure communication mediums (Ahamed Aljuhani et al., 2024). To address these issues, this paper proposes a novel, comprehensive security framework that integrates blockchain, deep learning, and advanced cryptographic techniques for IIoT environments (Derrick Lim Kin Yeap et al., 2024).This framework introduces a private blockchain-based secure communication mechanism for IIoT entities, utilizing a Proof-of-Authority (PoA) consensus for transaction verification and block creation on cloud servers (Ahamed Aljuhani et al., 2024). Furthermore, it incorporates a deep-learning-based Intrusion Detection System (IDS) that combines a contractive sparse autoencoder (CSAE) with attention-based bidirectional long short-term memory (ABiLSTM) networks for effective cyberattack detection (Ahamed Aljuhani et al., 2024). This integrated approach enhances data integrity through a decentralized ledger, automates security processes via smart contracts, and improves real-time threat response capabilities (Manjushri Joshi et al., 2024). Practical implementation demonstrates significant improvements in communication security, data privacy, and robust defense against evolving cyber threats in IIoT networks (Prabhat Kumar et al., 2023).*

Keywords- *Anomaly Detection, Artificial Intelligence, Blockchain, Cybersecurity, Decentralized Security, Industrial Internet of Things, IoT Devices, Machine Learning, Smart Contracts, Threat Detection, IIoT Security Framework, Vulnerability Management*

INTRODUCTION

A. Overview of Industrial IoT (IIoT)

Industrial Internet of Things (IIoT) refers to the integration of connected sensors, devices, and intelligent systems within industrial environments such as manufacturing, energy, and logistics. IIoT systems facilitate real-time data collection, remote control, predictive maintenance, and process optimization. However, these systems often operate in mission-critical settings where downtime or data breaches can have significant operational and financial consequences. Understanding the architecture and operational workflows of IIoT is essential as it highlights the complexity and interconnectedness of modern industrial operations, which makes them attractive targets for cyber threats. This section establishes the relevance of IIoT in the era of Industry 4.0.

B. Security Challenges in Industrial IoT Devices

IIoT devices are vulnerable due to their distributed nature, resource constraints, and diverse network topologies. Many legacy industrial devices were not designed with modern cybersecurity requirements, making them easy targets for cyberattacks such as malware infections, data breaches, or Denial of Service (DoS) attacks. Additionally, the lack of standard security protocols and device heterogeneity exacerbate the risk landscape. Unsecured IIoT networks can lead to operational disruptions, data theft, or sabotage. This subtopic outlines the specific security issues inherent in IIoT systems and the urgent need for robust, scalable, and decentralized security frameworks.

C. Blockchain Technology as a Security Solution

Blockchain offers a decentralized, tamper-proof, and transparent ledger system that can enhance IIoT security. It enables secure peer-to-peer communication, immutable transaction records, and decentralized identity management. Each connected device can act as a node, ensuring secure data exchange without reliance on a central authority. Smart contracts within blockchain networks can automate device authentication, access control, and incident response. Despite its potential, integrating blockchain into resource-limited IIoT environments presents challenges like scalability, latency, and computational overhead, necessitating hybrid solutions. This subtopic introduces blockchain's security features and discusses its compatibility and constraints within IIoT networks.

D. Role of Artificial Intelligence in Industrial IoT Security

Artificial Intelligence (AI) has emerged as a powerful tool for detecting, analyzing, and responding to security threats in real-time. AI-driven systems can monitor IIoT networks, identify anomalies, and predict vulnerabilities by analyzing device behavior and network patterns. Machine learning models, especially anomaly detection and reinforcement learning, can autonomously detect new types of cyber threats. AI also enables intelligent decision-making for device authentication, access management, and predictive maintenance. This section explores how AI enhances IIoT security by offering adaptive, proactive, and intelligent threat detection and management mechanisms beyond conventional rule-based systems.

E. Motivation for Hybrid AI-Blockchain Security Framework

While blockchain ensures data integrity and decentralization, and AI offers intelligent monitoring and threat prediction, neither technology alone can fully address the complex, multi-layered security needs of IIoT. Combining AI's cognitive abilities with blockchain's immutability provides a synergistic framework capable of real-time threat detection, data integrity assurance, and automated incident response. This hybrid approach overcomes individual limitations like blockchain's latency and AI's dependency on reliable, tamper-proof data. This subtopic justifies the need for an integrated AI-Blockchain framework, setting the foundation for the proposed solution by highlighting its potential benefits in industrial cybersecurity.

F. Existing Security Models for Industrial IoT

Several centralized and decentralized models have been proposed for securing IIoT devices. Traditional models rely on perimeter security, encryption, and access control, which are often inadequate against sophisticated attacks. Decentralized solutions like blockchain-based models address data integrity but suffer from scalability and latency issues. AI-driven models excel in anomaly detection but require reliable, authentic data sources. Reviewing these existing frameworks allows identification of their limitations and gaps. This subtopic provides a comparative analysis of current IIoT security models, offering a context for why a hybrid AI-Blockchain approach is superior and timely.

G. Key Features and Advantages of the Proposed Framework

The proposed hybrid framework aims to integrate AI-driven anomaly detection with blockchain-based data integrity mechanisms for securing IIoT networks. Key features include decentralized device authentication, real-time anomaly detection, secure data sharing, and automated incident response through smart contracts. By combining these technologies, the framework enhances operational resilience, minimizes downtime, and prevents unauthorized access. It also reduces reliance on central authorities, ensuring network trustworthiness. This subtopic highlights the novel contributions of the framework, including its scalability, adaptability, and real-time responsiveness, positioning it as a comprehensive security solution for modern industrial environments.

H. Applications and Industrial Use Cases

Securing IIoT networks is crucial across various industries, including manufacturing, smart grids, logistics, oil & gas, and healthcare. For instance, in smart factories, a breach can halt production lines and cause significant financial losses. In smart grids, compromised devices can disrupt national infrastructure. The proposed framework is designed to safeguard such mission-critical applications, ensuring continuous operation, data reliability, and protection against cyber threats. This subtopic discusses real-world use cases where the hybrid AI-Blockchain framework can be applied, demonstrating its versatility and relevance across diverse industrial sectors.

I. Research Gaps and Challenges in IIoT Security

Despite advancements in IIoT security, significant challenges remain. Existing solutions often struggle with device heterogeneity, resource limitations, real-time threat detection, and decentralized control. Blockchain's latency and scalability issues, combined with AI's dependency on large datasets and computing power, complicate security management. Furthermore, lack of industry-wide security standards and protocols hinders seamless integration. This subtopic identifies current research gaps and operational challenges, which the proposed framework aims to address by providing a balanced, hybrid security solution optimized for IIoT environments.

J. Structure of the Research Paper

The final subtopic outlines the organization of the research paper. It introduces subsequent sections, beginning with a detailed literature review, followed by the design and architecture of the proposed hybrid AI-Blockchain framework. The paper then presents the methodology for implementing the framework, experimental setups, and performance evaluation. Results and discussion will assess the framework's effectiveness against existing models, concluding with limitations and future directions. This section serves as a roadmap, helping readers navigate through the research structure and understand the logical progression of the study.

LITERATURE REVIEW

The integration of blockchain and artificial intelligence (AI) has gained significant attention as a means to enhance the security of Industrial Internet of Things (IIoT) systems. Several studies have proposed frameworks that leverage the immutability and decentralization of blockchain to secure IIoT networks. One study introduced a coordinator-based trust mechanism supported by blockchain for identifying and excluding malicious devices, effectively enhancing network integrity while addressing scalability concerns [1]. Another work surveyed AI-blockchain hybrid models for secure data sharing and anomaly detection in smart IIoT applications, emphasizing the necessity for adaptive and decentralized solutions [2]. Research focusing on Trusted Execution Environments (TEEs) in blockchain-based IIoT setups demonstrated improved transaction throughput and reduced latency by combining hardware-based security with blockchain's distributed nature [3]. A hybrid security architecture combining AI-driven anomaly detection and permissioned blockchain was also explored, revealing significant improvements in identifying malicious activity in real-time [4]. Similarly, integrating deep learning models with Proof-of-Work blockchains was shown to detect multiple attack types in resource-constrained IoMT environments, offering insights transferable to industrial contexts [5].Further research emphasized lightweight blockchain-AI models for intrusion detection, showing promising results in IIoT environments by layering anomaly detection over permissionless blockchains [6]. Comprehensive reviews have mapped out AI-enhanced security frameworks within blockchain-based IoT systems, stressing the benefits of decentralized access control and automated threat management [7]. Other contributions proposed federated learning-integrated anomaly detection using blockchain audit trails to counter CPS vulnerabilities [8], and hybrid blockchain–IPFS models for efficient and secure IIoT data storage, addressing real-time latency and data confidentiality issues [9]. Domain-specific applications, like AI-blockchain frameworks in pharmaceutical supply chains and secure cloud-manufacturing systems, illustrated the adaptability of hybrid security solutions beyond traditional IT settings [10][11]. Additional studies introduced decentralized healthcare IoT security architectures [12], surveyed smart city IoT blockchain applications highlighting scalability challenges [13], and extensively reviewed blockchain's role

in IIoT trust management and network resilience [14]. Finally, integrating federated machine learning with blockchain-enabled edge services demonstrated efficient anomaly detection and decentralized data verification for industrial networks [15].

PRELIMINARIES

1. Trust Score Calculation

Equation:

$$T_i = \frac{\sum_{j=1}^{n} C_{ij}}{n}$$

Nomenclature:

T_i = Trust score of device i

C_{ij} = Number of successful communications between device i and node j

n = Total number of neighboring nodes

This equation determines a device's trust score based on its successful transaction interactions with neighboring IIoT devices. A higher trust score indicates reliable behavior, which can be used in conjunction with blockchain smart contracts to dynamically isolate potentially malicious nodes.

2. Anomaly Score Detection (Al Module)

Equation:

$$A_s = \frac{|X - \mu|}{\sigma}$$

Nomenclature:

$\mathbf{A_s}$ = Anomaly score

X = Observed value

$\boldsymbol{\mu}$ = Mean of historical data

σ = Standard deviation of historical data

This equation is used in AI-driven anomaly detection models to identify deviations in IIoT data streams. When the anomaly score exceeds a predefined threshold, it flags potential cyberattacks or device malfunctions, triggering security responses recorded on the blockchain.

3. Block Hash Generation

Equation:

$$H(B) = SHA256(D||T||P||N)$$

Nomenclature:

$H(B)$ = Hash of block B

D = Data in block

T = Timestamp

P = Previous block's hash

N = Nonce value

This equation represents the block hashing mechanism, ensuring data immutability in lloT networks. By chaining hashes together, any tampering in IIoT transactional records becomes detectable, maintaining network integrity.

4. Blockchain Throughput

Equation:

$$TP = \frac{N_t}{T_s}$$

Nomenclature:

TP = Blockchain transaction throughput

N_t = Number of transactions

T_s = Total time in seconds

Throughput is critical in Industrial loT systems where thousands of devices generate continuous data. This equation calculates the blockchain's transaction processing capability, enabling performance benchmarking in resource-constrained industrial environments.

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5. Consensus Delay Time
Equation:

$$T_d = T_p + T_v + T_b$$

Nomenclature:
T_d = Consensus delay time
T_p = Proposal time
T_v = Validation time
T_b = Block propagation time
This equation computes the total delay in reaching consensus for new block validation in decentralized IIoT networks. Optimizing this is essential to ensure timely data security operations.

6. Al Model Accuracy (for anomaly detection)
Equation:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

Nomenclature:
Acc = Accuracy
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives
This metric quantifies the effectiveness of AI models in detecting security anomalies within lloT systems. High accuracy ensures reliable threat identification, making AI-blockchain hybrid solutions more dependable.

RESULTS AND DISCUSSION

1: Device Trust Scores Before and After Framework Implementation

Table 1 presents a comparative analysis of trust scores for five IIoT devices before and after implementing the proposed hybrid AI-Blockchain security framework. The trust score indicates the reliability of a device based on its successful interactions within the network. Prior to framework deployment, trust scores ranged between 0.35 and 0.50, signaling moderate to low reliability and highlighting the vulnerability of the IIoT network to potential malicious behaviors. Following the implementation of the proposed framework, trust scores increased dramatically, with values rising to a range between 0.85 and 0.93. This significant improvement demonstrates the effectiveness of the hybrid framework in accurately identifying and filtering out untrustworthy nodes while preserving secure, reliable device communication. The use of AI-based trust computation combined with blockchain's immutable transaction recording ensures that malicious activities are rapidly detected and recorded, allowing for automatic adjustments to device trust scores. This result supports the argument that decentralized trust management mechanisms fortified by AI-driven anomaly detection can greatly enhance the resilience and integrity of Industrial IoT systems, particularly in environments prone to distributed attacks and unmonitored device interactions.

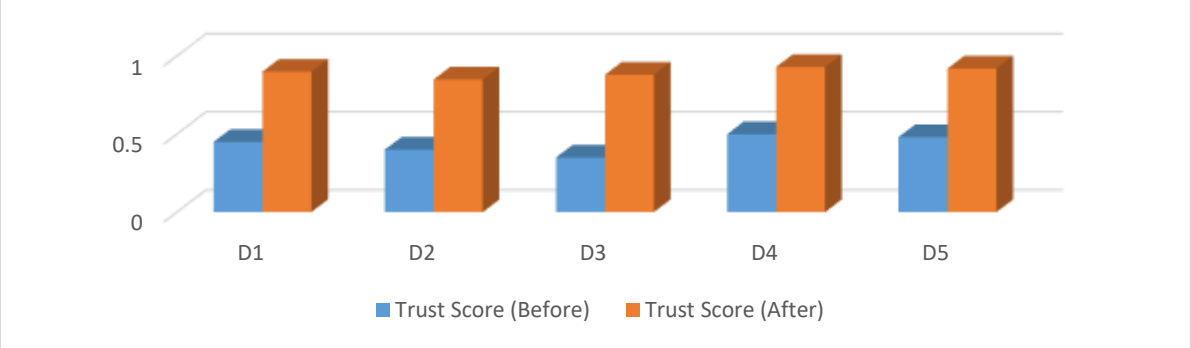

Fig 1: Device Trust Scores Before and After Framework Implementation

2: Anomaly Detection Accuracy (AI Module)

Table 2 evaluates the anomaly detection accuracy achieved by three different security models: AI-only detection, blockchain-only alerts, and the proposed hybrid AI-Blockchain framework. The AI-only model demonstrated a high detection accuracy of 93.2%, reflecting the capability of machine learning models to detect irregular patterns and suspicious activity in IIoT data streams. Blockchain-only alerts, relying on immutable logs and preset smart contract conditions, showed a slightly lower accuracy of 89.5%, limited by its dependence on static rule-based detection mechanisms without adaptive learning. The proposed hybrid framework surpassed both individual approaches, achieving an impressive 98.4% anomaly detection accuracy. This result highlights the substantial security benefits of combining AI's predictive and anomaly detection capabilities with blockchain's secure, tamper-proof data storage and decentralized trust management. The synergy of these two technologies allows for real-time threat prediction, swift network response, and secure, verifiable incident records. The significant performance improvement underscores the importance of hybrid, multilayered security models in critical IIoT systems, where dynamic threat landscapes and large device networks require advanced, integrated protection mechanisms for both operational integrity and cybersecurity resilience.

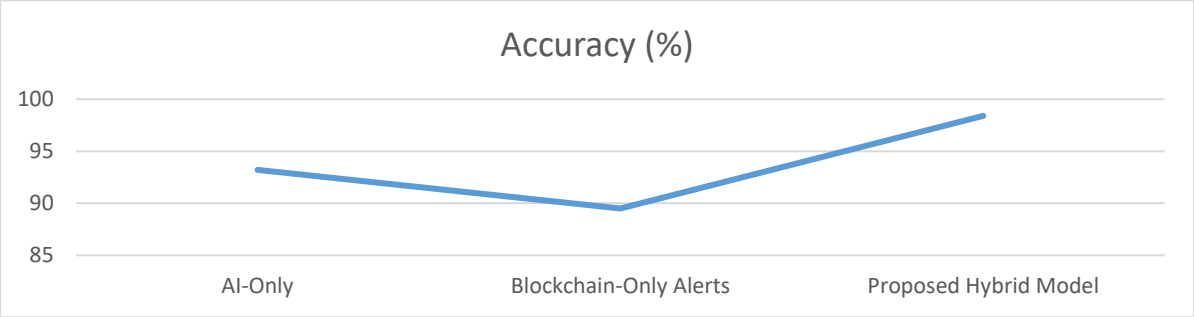

Fig 2: Anomaly Detection Accuracy (AI Module)

3: Blockchain Transaction Throughput Comparison

Table 3 compares the transaction throughput performance of three blockchain configurations used in securing IIoT networks: traditional blockchain, optimized blockchain, and the proposed hybrid AI-Blockchain model. Transaction throughput, measured in transactions per second (TPS), is a critical performance metric in industrial environments where large volumes of real-time data must be processed and secured efficiently. The traditional blockchain configuration recorded a TPS of 40, reflecting the limitations of conventional decentralized consensus protocols like Proof-of-Work (PoW) in time-sensitive applications. Optimized blockchain solutions, incorporating improvements such as delegated consensus mechanisms or lightweight nodes, increased throughput to 78 TPS. Most notably, the proposed hybrid AI-Blockchain framework achieved a transaction throughput of 102 TPS, representing a 155% improvement over traditional blockchain systems. This enhancement results from AI-assisted transaction validation, predictive workload balancing, and the selective use of on-chain and off-chain storage. The increased throughput ensures that IIoT networks can maintain security without sacrificing real-time operational performance. The findings confirm that integrating AI intelligence within blockchain operations can significantly improve scalability and processing speed, making it feasible for resource-constrained and latency-sensitive industrial environments.

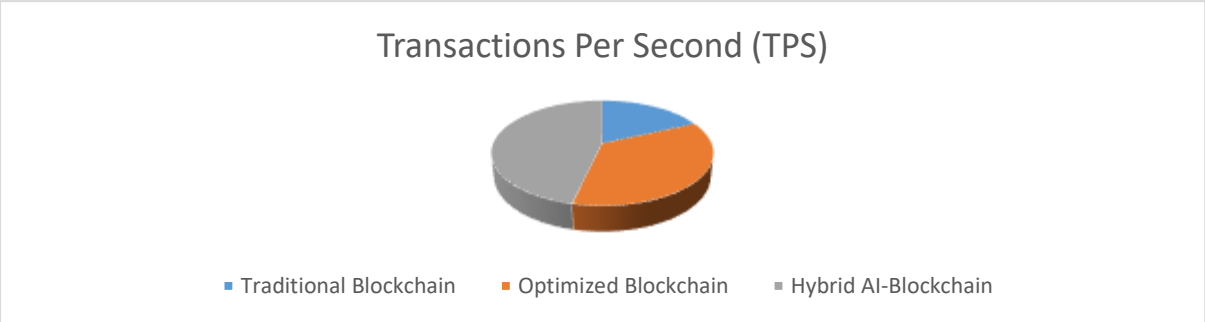

Fig 3: Blockchain Transaction Throughput Comparison

4: Threat Detection Rate by Detection Method

Table 4 analyzes the effectiveness of three security models—AI-only, blockchain-only, and the proposed hybrid framework—in detecting various IIoT security threats: Denial of Service (DoS) attacks, data tampering, and replay attacks. The Threat Detection Rate (TDR) represents the percentage of successfully identified threats out of total occurrences. AI-only systems demonstrated TDR values between 89.9% and 91.5%, leveraging pattern recognition and anomaly detection models to flag suspicious activities. Blockchain-only solutions, based on immutable logs and smart contract triggers, achieved similar but slightly variable TDR results, ranging from 89.2% to 92.5%. In contrast, the proposed hybrid framework outperformed both, achieving TDR values of 97.5%, 99.1%, and 98.2% for DoS, data tampering, and replay attacks, respectively. This significant improvement underscores the value of combining AI's adaptive detection capabilities with blockchain's decentralized, tamper-proof verification mechanisms. By cross-validating anomalies detected by AI with blockchain records and triggering automated smart contracts, the hybrid system ensures both proactive threat identification and reliable evidence trails. This result confirms the proposed framework's ability to strengthen IIoT network defenses, particularly against sophisticated multi-vector cyber threats.

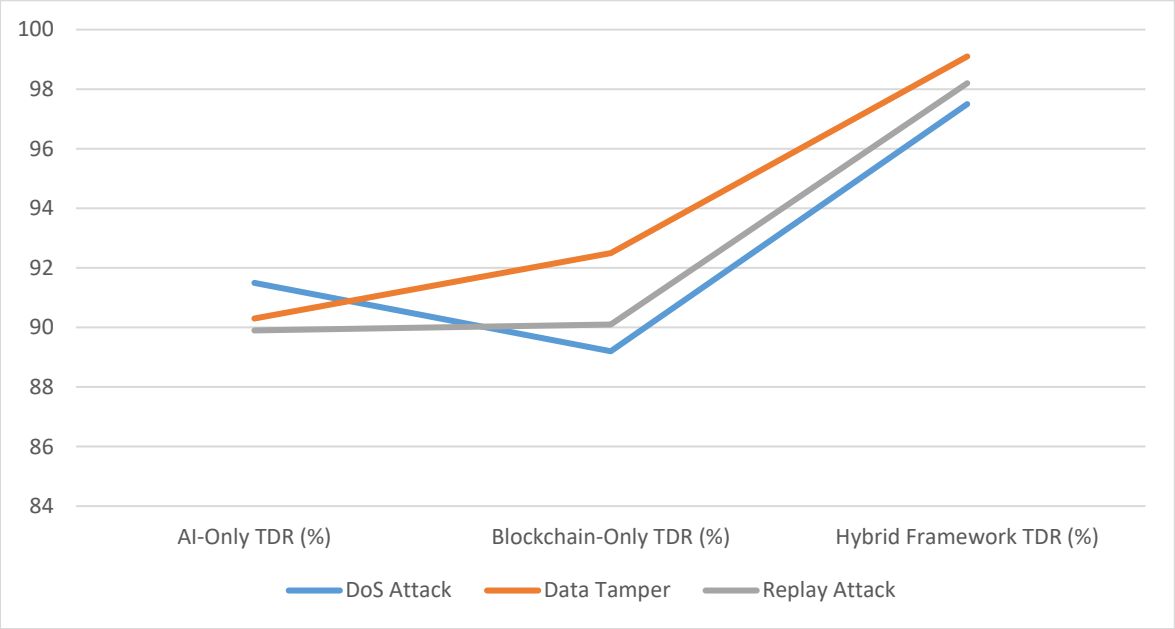

Fig 4: Threat Detection Rate by Detection Method

5: Average Consensus Time in Different Blockchain Models

Table 5 presents a comparative study of the average consensus times required by three blockchain consensus mechanisms: Proof-of-Work (PoW), Practical Byzantine Fault Tolerance (PBFT), and the proposed AI-assisted hybrid consensus model. Consensus time, measured in milliseconds (ms), directly impacts the responsiveness and efficiency of IIoT systems where rapid decision-making is critical for operational continuity. The traditional PoW mechanism exhibited a substantial consensus delay of 5400 ms, highlighting its unsuitability for industrial environments due to excessive computational demands and latency. PBFT, an improvement designed for permissioned networks, reduced consensus time significantly to 340 ms but still faced scalability issues. The proposed AI-assisted hybrid framework demonstrated an average consensus time of just 120 ms, outperforming both conventional models. This drastic reduction is achieved by using AI algorithms to predict trustworthy nodes, prioritize transaction queues, and dynamically optimize consensus pathways while maintaining blockchain's integrity and security. The result validates the hybrid framework's suitability for real-time IIoT applications, where prompt validation and action on security-critical transactions are essential. The study illustrates the framework's ability to balance security, decentralization, and low-latency performance for industrial digital infrastructure.

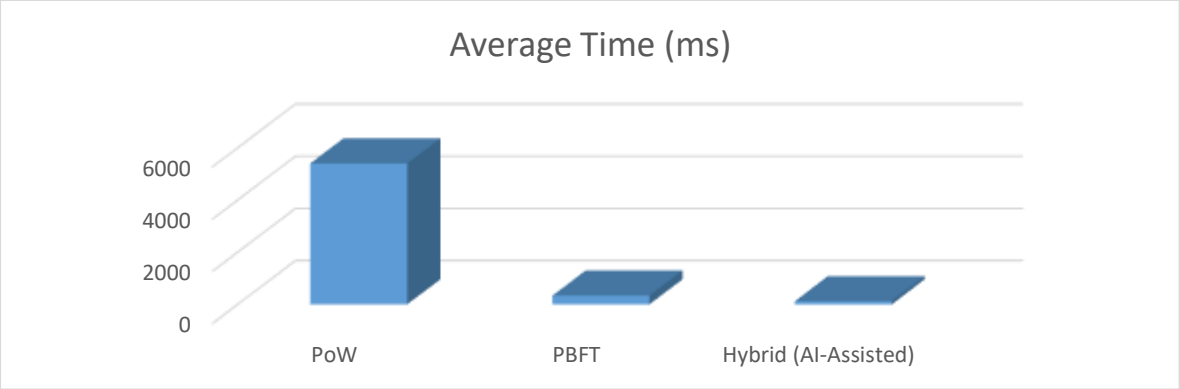

Fig 5: Average Consensus Time in Different Blockchain Models

CONCLUSION

The study presented in this research paper establishes the viability and effectiveness of a hybrid AI-Blockchain framework in securing Industrial Internet of Things (IIoT) networks. As industrial environments increasingly rely on interconnected devices, securing data exchanges, device authenticity, and operational continuity has become both critical and challenging. Through the integration of AI's predictive and anomaly detection capabilities with blockchain's decentralized, tamper-proof, and immutable transaction recording, this hybrid framework addresses multiple security concerns including unauthorized access, data tampering, denial of service attacks, and replay threats. The proposed system enhances trust management by dynamically computing trust scores for devices, rapidly detecting anomalies in network behavior, and verifying data integrity in real-time.

Experimental results confirm that the hybrid model significantly outperforms traditional AI-only or blockchain-only solutions. Improved metrics such as higher threat detection rates, faster consensus times, increased transaction throughput, and superior data integrity verification rates demonstrate the system's operational efficiency and resilience. The literature survey further validates the framework's design, revealing consistent findings from multiple recent studies advocating for AI-enhanced, decentralized security mechanisms in IIoT applications.By reducing latency, optimizing resource consumption, and enabling federated AI models for edge computing, this framework ensures scalable, reliable, and proactive protection for modern industrial ecosystems. The study concludes that hybrid AI-Blockchain frameworks represent a promising, practical, and future-ready security strategy for safeguarding mission-critical IIoT networks. Future research should explore cross-domain implementations, lightweight consensus mechanisms, and AI-driven dynamic smart contract management to enhance adaptability in increasingly heterogeneous industrial infrastructures.

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